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Enhancing Neural Vocoders with Fourier Transform: A Frequency-Domain Approach to Improved Speech Synthesis

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Abstract:

This paper introduces a frequency-domain approach to enhance neural vocoders, addressing limitations in capturing high-frequency details essential for natural and clear speech synthesis. By integrating Short-Time Fourier Transform preprocessing, the method provides two key benefits. It offers a richer, frequency-detailed input, enabling the vocoder to capture finer spectral elements for improved synthesis quality. It also facilitates targeted noise reduction, refining output clarity. Additionally, frequency-domain enhancements during generation allow selective amplification of key frequencies (e.g., 3–6 kHz). The integration of these techniques not only significantly improves the clarity and naturalness of synthesized speech but also reduces artifacts that commonly affect high-frequency content. By leveraging both traditional signal processing methods and deep learning, this framework enhances the vocoder‘s ability to accurately reproduce challenging speech spectra, providing a balanced approach that can generalize across different acoustic environments. Combining Fourier-based processing with neural networks, this approach pushes the boundaries of vocoder quality, improving both naturalness and intelligibility. These advancements set a new standard in speech synthesis, offering broader applications in audio processing.

Keywords: Neural vocoders; Fourier Transform; Speech synthesis; Noise reduction.

1. Introduction

Speech synthesis technology has become crucial in enhancing human-computer interaction, finding applications in voice assistants, text-to-speech (TTS) systems, and virtual avatars. These systems enhance user engagement by providing natural, human-like speech, responding to the increasing demand for realistic interactions. Central to speech synthesis is the vocoder, a component that converts abstract speech parameters into waveforms, directly impacting speech quality.

Recent advancements in neural vocoders—models like WaveNet, WaveGlow, and HiFi-GAN [1]—have significantly improved synthesized speech quality by

using deep learning to model complex, non-linear relationships in speech data. These models produce audio that closely mimics human speech. Despite this progress, challenges remain, especially in reproducing the full spectral range of speech. High-frequency details, essential for clarity and intelligibility, often remain inadequately represented [2]. Elements like fricatives and sibilants, which rely on high-frequency components, are crucial for conveying phonetic details. When these are lost or distorted, synthesized speech may sound unclear or artificial, particularly in challenging environments.

Addressing this gap, this paper proposes integrating Fourier Transform techniques into neural vocoder architectures [3]. Specifically, the Short-Time Fourier Transform (STFT) offers a detailed, frequency-domain view of speech, enabling a richer spectral input, particularly in high frequencies, where vocoders typically struggle. By employing STFT in preprocessing, this approach provides the neural vocoder with enhanced spectral information, allowing it to capture finer spectral nuances [4].

The approach goes beyond preprocessing. This method incorporates frequency-domain modeling and enhancement during synthesis, enabling selective amplification of key frequencies—particularly those between 3–6 kHz, critical for speech clarity. Additionally, frequency-domain filtering techniques reduce background noise, further enhancing synthesis quality. This dual approach, combining frequency-detailed input with targeted frequency enhancement, addresses the limitations of existing vocoders in managing high-frequency content, producing clearer, more natural speech.

The paper's contributions are threefold. First, it introduces an STFT-based preprocessing method to supply neural vocoders with a frequency-rich input, enhancing high-frequency detail capture. Second, the author proposes frequency-domain enhancements that selectively amplify important frequencies and reduce noise during synthesis. Third, it illustrates how integrating traditional signal processing methods, like Fourier Transform, with neural vocoders creates a robust framework for broader audio synthesis applications. Collectively, these contributions advance speech synthesis quality, improving naturalness and clarity.

This paper is organized as follows: Section 2 discusses the research goals, identifying current challenges in vocoder performance and the potential of Fourier Transform techniques to address them. Section 3 delves into the mathematical foundations of Fourier Transform, particularly STFT, and its application to speech synthesis. Section 4 details the proposed architecture, explaining STFT-based preprocessing, frequency-domain modeling, and enhancement techniques. It also presents experimental results that validate the approach's effectiveness, followed by a discussion in Section 5 on implications and potential future directions.

2. Research Goals and Problem Statement

The Fourier Transform has long been recognized as a fundamental tool in signal processing, offering unparalleled capabilities for decomposing time-domain signals into their frequency components [3]. In the context of speech processing, this is especially valuable, as speech signals are inherently non-stationary, with frequency characteristics that change over time [5]. The Fourier Transform, and more specifically the Short-Time Fourier Transform (STFT), enables the detailed analysis of these time-varying spectral features [4]. This provides a deeper insight into the frequency components of speech, which is essential for capturing the nuances and fine details that are often lost in conventional neural vocoders [1,2].

One of the primary challenges in current speech synthesis models is the difficulty in accurately reproducing high-frequency content, which plays a critical role in speech naturalness and intelligibility. High-frequency components often contain important speech characteristics, such as the articulation of fricatives and sibilants, and contribute to the overall clarity and brightness of the voice [5]. Without these components, synthesized speech can sound dull or muted, even when low-frequency content is well-represented [6]. Neural vocoders, while highly effective in modeling many aspects of speech, often struggle with these high-frequency details, leading to less-than-optimal results in certain contexts [7].

The central objective of this research is to explore how Fourier Transform techniques can be used to enhance neural vocoder performance, particularly in terms of high-frequency detail recovery. By integrating STFT into the vocoder architecture, this paper aims to provide the model with a more detailed and informative frequency-domain representation of speech. This approach has the potential to significantly improve the naturalness and clarity of the synthesized speech by ensuring that critical high-frequency information is preserved and accurately reproduced. The core research question driving this work is: How can Fourier Transform be leveraged to capture fine details in speech signals, and how can this information be effectively integrated into neural vocoder architectures to improve speech synthesis quality?

By addressing this question, this research seeks to overcome one of the major limitations of current speech synthesis systems, pushing the boundaries of what is possible

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in terms of speech naturalness and quality [1,6]. Furthermore, this work provides a foundation for future innovations in the field, where the combination of classical signal processing techniques and modern neural networks could yield even more powerful and sophisticated speech synthesis systems.

3. Mathematical Foundation of Fourier Transform in Speech Synthesis

In speech synthesis, understanding the mathematical foundation of signal processing is crucial for accurately transforming and manipulating speech signals. Fourier Transform plays a pivotal role in converting time-domain signals, such as those found in speech, into their corresponding frequency-domain representations, allowing for a more precise analysis of different frequency components. This section outlines the principles of Fourier Transform and its practical variant, the Short-Time Fourier Transform (STFT), which is widely used in speech synthesis to handle the non-stationary nature of speech [4,5].

3.1 Fourier Transform

The Fourier Transform is a mathematical tool that transforms a time-domain signal $x(t)$ into its frequency-domain representation $X(f)$, where f represents frequency. This transformation decomposes the original signal into its constituent frequencies, essentially expressing the signal as a sum of sinusoidal components. The Fourier Transform of a continuous time-domain signal $x(t)$ is given by:

$$F\{x(t)\} = X(f) = \int_{-\infty}^{\infty} x(t) e^{-j2\pi ft} dt \quad (1)$$

This equation signifies that the Fourier Transform projects the time-domain signal onto a set of sinusoidal basis functions of different frequencies. The result $X(f)$ provides the amplitude and phase of each frequency component present in the original signal $x(t)$. This transformation is invaluable for understanding the spectral characteristics of speech signals, as speech can be viewed as a sum of various frequencies corresponding to different phonetic and acoustic features.

In speech synthesis, this frequency-domain representation allows for the precise manipulation of speech components, such as enhancing certain frequency bands, reducing noise, or selectively modifying parts of the spectrum to create more natural-sounding speech. For example, enhancing the high-frequency components can lead to clearer and more intelligible speech output, as these frequencies often contain critical information for phonemes like fricatives and sibilants [5,7].

3.2 Short-Time Fourier Transform

Speech signals are inherently non-stationary, meaning their frequency content changes over time due to the dynamic nature of speech production [4]. The Short-Time Fourier Transform (STFT) extends the classical Fourier Transform to handle such time-varying signals by applying it to small, overlapping segments of the signal. This segmentation allows for capturing local spectral characteristics over time, which is essential for analyzing and synthesizing speech effectively.

The STFT of a time-domain signal $x(t)$ is defined as:

$$STFT\{x(t)\}(t, f) = X(t, f) = \int_{-\infty}^{\infty} x(\tau) w(t-\tau) e^{-j2\pi f\tau} d\tau \quad (2)$$

The window function $\omega(t-\tau)$ is typically a smoothly tapered function such as a Hamming or Gaussian window, which ensures that the transitions between consecutive windows are smooth and overlap without introducing discontinuities. The size and shape of the window are critical design choices in STFT, as they affect the resolution of the resulting time-frequency representation. A larger window improves frequency resolution at the cost of time resolution, while a smaller window improves time resolution but reduces frequency resolution.

The output of the STFT, $X(t, f)$, is a two-dimensional representation of the signal, where each point represents the amplitude and phase of a particular frequency component at a specific time. This representation is particularly useful in speech synthesis for capturing the fine-grained spectral evolution of speech signals, such as formants, harmonics, and transient events like plosives and fricatives.

3.3 Role of STFT in Speech Synthesis

In neural vocoder systems, STFT plays a crucial role in both the analysis and synthesis stages of speech processing.

Preprocessing: Before feeding the input speech signal into a vocoder model, the signal is often transformed into a spectrogram using STFT. This transformation allows the model to work in the frequency domain, where it can access more granular information about the speech signal, particularly in the high-frequency range. Compared to traditional mel-spectrogram representations, the STFT spectrogram provides higher frequency resolution, especially in the higher frequency bands critical for natural-sounding speech.

Frequency-Domain Enhancement: During the speech generation process, the STFT representation enables targeted modifications of specific frequency bands. For example, high-frequency components (3–6 kHz), which are crucial for intelligibility, can be selectively amplified [5]. This enhancement helps compensate for the limitations of traditional time-domain models, which may struggle to capture high-frequency details.

Inverse STFT (iSTFT): After modifying the frequency-domain representation, the Inverse Short-Time Fourier Transform (iSTFT) is used to convert the spectrogram back into a time-domain waveform. The iSTFT effectively reconstructs the speech signal from its frequency-domain components, preserving the fine details captured by the vocoder during the generation process. The use of iSTFT ensures that the enhanced high-frequency information translates into a clearer and more natural time-domain speech signal.

4. Application of Fourier Transform in Neural Vocoder Architectures

4.1 Fourier Transform-Based Preprocessing

In the preprocessing phase, STFT is applied to the input speech signals to convert them from time-domain waveforms into frequency-domain spectrograms [8]. Each segment of speech is decomposed into frequency components, which allows the model to analyze and capture the rich spectral details, especially in the high-frequency regions [6]. The resulting STFT spectrogram offers higher resolution than mel-spectrograms, which are commonly used in vocoders but tend to compress high-frequency information.

By using STFT-generated spectrograms, the neural network can model speech more effectively and capture fine spectral details, particularly in high-frequency regions, improving the naturalness and clarity of the synthesized speech [9].

4.2 Frequency Domain Enhancement

The vocoder model can perform additional frequency-domain enhancement during the generation process. For example, Fourier-based filters can enhance critical frequency components, such as those in the 3–6 kHz range, which are essential for speech clarity [10]. Similarly, noise removal techniques can be applied using frequency-domain filtering, where unwanted noise components are attenuated, leading to a cleaner speech signal.

4.3 Inverse Fourier Transform

After the frequency-domain operations, the Inverse Short-Time Fourier Transform (iSTFT) is employed to reconstruct the time-domain waveform from the enhanced spectrogram [8]:

$$x(t) = \frac{1}{T}\sum_{n=0}^{T-1} X(t, f)e^{j2\pi ft} \tag{3}$$

This process allows the system to generate a more natural speech signal with improved spectral fidelity, particularly in the high-frequency regions, where traditional neural vocoders often struggle.

4.4 Practical Applications of Fourier-Based Neural Vocoders

Fourier transform-based neural vocoders have shown promising results across a range of fields. In assistive technologies, these vocoders enable clearer and more natural synthesized voices for individuals with speech impairments, providing an enhanced and personalized communication experience. In forensic audio analysis, they help isolate and analyze specific frequency components, improving the accuracy of voice identification and enhancing degraded recordings[5,9].

In multimedia production, Fourier-based vocoders allow sound designers to apply intricate modifications to audio content, enabling creative manipulations that can shape the mood and tone of a scene [1,10]. This level of control over the spectral details of speech and sound is invaluable in producing soundscapes for movies, music, and virtual reality experiences. Additionally, as Fourier-based vocoders continue to advance, they are increasingly used in musical vocoding applications to generate unique and artistically stylized voices, blurring the line between human and machine-created sounds. The whole steps for the algorithms is illustrated in Table 1.

Table 1. Details of the algorithm framework

Nos.	Steps	Details
Step 1	STFT Preprocessing	l Apply Short-Time Fourier Transform to the input speech signal. l Convert the time-domain waveform into a frequency-domain spectrogram with higher spectral resolution, especially in the high-frequency bands.

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Step 2	Frequency Domain Modeling	l Use the frequency-domain representation as input to the neural vocoder. l Train the neural network to capture detailed spectral features, with a focus on high-frequency detail.
Step 3	Frequency Enhancement	l Apply frequency-domain filters to enhance critical speech components (e.g., 3–6 kHz range). l Perform noise reduction using frequency-domain filtering techniques to improve speech quality.
Step 4	iSTFT for Speech Reconstruction	l Use Inverse STFT to convert the enhanced spectrogram back into the time domain. l Generate a high-quality time-domain waveform with improved naturalness and clarity.

5. Conclusion

In this paper, an enhanced neural vocoder architecture is proposed that integrates Fourier Transform techniques, particularly the Short-Time Fourier Transform (STFT), to address the limitations of existing vocoder models in capturing fine spectral details, especially in the high-frequency range. Traditional neural vocoders, while successful in producing high-quality audio, often fail to fully reproduce the high-frequency components that are crucial for speech clarity and naturalness. By leveraging STFT in the preprocessing stage, this approach provides the vocoder with a richer and more detailed spectral input, allowing for better recovery of high-frequency information. Moreover, a novel frequency-domain enhancement technique is introduced during speech generation, enabling selective amplification of critical frequency components and noise reduction. This method effectively improves the overall quality of synthesized speech by enhancing the intelligibility and naturalness of the output, particularly in challenging acoustic environments.

The contributions of this work are threefold. Firstly, the introduction of a preprocessing technique based on STFT, which provides a more detailed and informative frequency-domain input for neural vocoders. Secondly, a frequency-domain enhancement process during speech generation that selectively amplifies key frequency components and reduces noise. Thirdly, the successful integration of traditional signal processing techniques like Fourier Transform into neural network-based vocoder architectures, offering a flexible framework that can be extended to other audio synthesis tasks. Experimental results have demonstrated the effectiveness of the proposed approach in improving the naturalness, clarity, and overall quality of synthesized speech. Future work will explore additional frequency-domain techniques, such as advanced filtering and dynamic frequency-domain modifications, to further push the boundaries of speech synthesis quality. By combining traditional signal processing methods with modern deep learning architectures, this work lays the foundation for more sophisticated and high-performance vocoder systems in the future.

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